

Appendix 2. The procedure of applying spatiotemporal  $Gi^*$  statistic in this study.

In this study, the spatiotemporal  $Gi^*$  statistic may identify hotspots at a designated week relative to the past few weeks' incidence and can be written as follows:

$$G_i^*(d, t) = \frac{\sum_{t=0}^m \sum_{j \in \partial i} w_{ij}(d, t) \cdot x_{jt} - \bar{x} \sum_{t=0}^m \sum_{j \in \partial i} w_{ij}(d, t)}{S \sqrt{\frac{n \sum_{t=0}^m \sum_{j \in \partial i} w_{ij}^2(d, t) - (\sum_{t=0}^m \sum_{j \in \partial i} w_{ij}(d, t))^2}{n-1}}} \quad (1)$$

where  $x_j$  is the weekly local COVID-19 incidence of district  $j$ ,  $\partial i$  denotes the set of spatial neighbors of district  $i$  (including district  $i$ ),  $m$  is the designated time lag,  $n$  is the number of spatiotemporal neighbors of district  $i$  (including location  $i$ ),  $\bar{x}$  and  $S$  represent the mean and the standard deviation of weekly local COVID-19 incidence of the set of spatiotemporal neighbors of district  $i$  (including district  $i$ ), respectively.

The spatiotemporal weight for neighbor  $j$  from district  $i$ ,  $w_{ij}(d, t)$ , is defined as follows:

$$w_{ij}(d, t) = (1 - \frac{d_{ij}}{\sum_{j \in \partial i} d_{ij}})^{t+1}, j \in \partial i, \quad (2)$$

where  $d_{ij}$  is the distance between locations  $i$  and  $j$ .

Owing to the spatiotemporal structure of the data, neighboring locations exist both in time and space. In this study, polygon contiguity, which means that two spatial units share a common border of non-zero length, is used to define the neighborhood size in space. To define temporal neighbors, time-lagged correlations, which describe how

similar the time series is with itself, are calculated and tested until the first statistically insignificant result appears with a significance level of 0.05. The result of the time lag selection here was eight weeks.